# ARTIFICIAL NEURAL NETWORK & PATTERN RECOGNITION APPROACH FOR NARROWBAND SIGNAL EXTRACTION

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Abstract: Estimation of unknown frequency, extraction of narrowband signals buried under noise and periodic interference are accomplished by employing the existing techniques. However, this paper proposes an artificial neural net based scheme together with pattern classification algorithm for narrowband signal extraction. A three layer feedforward net is trained with three different algorithms namely backpropagation, Cauchy's algorithm with Boltzmann's probability distribution feature and the combined backpropagation-Cauchy's algorithm. Constrained tangent hyperbolic function is used to activate individual neuron. Computer simulation is carried out with inadequate data to reinforce the idea of net's generalization capability. The robustness of the proposed scheme is claimed with the results obtained by making 25% links faulty between the layers. Performance comparison of the three algorithms is made and the superiority of the combined backpropagation-Cauchy's algorithm is established over the other two algorithms. Simulation results for a wide variety of cases are presented for better appraisal.

## INTRODUCTION

Recent age has witnessed the rapidly growing interest of researchers to employ novel and robust algorithms to separate the desired signal from the undesired ones. The urge for real time implementation served as catalyst for the development of robust adaptive algorithms to work well in the non-stationary environment. Although the adaptive systems is a key idea to solve the real world problems, still in some complex situations the algorithms employed fail to adjust their parameters autonomously thereby leading to intractability of the problem. During the past two decades various adaptive techniques with necessary algorithms were employed for efficient noise cancellation, frequency estimation, narrowband signal extraction, etc. [1]. However, the inherent limitations of the existing adaptive systems constrained the researchers' application domain.

The challenge encountered for the above problems motivated the researchers to switch over to the field of artificial neural network(ANN). The network's capabilities like learning, generalization strengthened the idea to the application domains like pattern detection, image recognition, target detection and handwritten character recognition [2,3,4], etc. In addition, the potentials of the neural nets encouraged the researchers to apply to the field of signal processing; particularly to narrowband signal extraction, spectral estimation, noise filtering [5,6,7], etc. The research papers reported so far employed backpropagation, Cauchy's algorithm [8,9,10] for learning of the net. Also quite interesting improvements are made in the learning of the net [11]. This paper presents a neural net based scheme as a viable solution for signal extraction. The scheme employs pattern classification algorithm in conjunction with the neural network to make the proposed method more flexible and robust. The convergence time and local minima trapping aspects are improved by employing the combined backpropagation- Cauchy's algorithm, in addition to backpropagation and Cauchy's algorithm. Tangent hyperbolic function constrained to operate in the non-linear zone is used to activate the individual processing element in the network. Exhaustive computer simulation is carried out to validate the attributes of the net like fault tolerance, generalization capability and extraction from inadequate data, etc. A performance comparison is also made for all the algorithms to exhibit the excellence of the combined algorithm over the other two.

## ANN & PATTERN RECOGNITION

Neurocomputing is the discipline concerned with parallel, distributed, adaptive information processing systems. The primary information processing system is the neural network. The attractive properties of the neural network fascinates most researchers to investigate the subject in depth and to fit into their application areas. The network may be single layer or multilayer but the latter is being preferred for its better representational capability and decision making. Mostly, a three layer net, consisting of a input, hidden and output layer, as shown in fig. 1, is used. The network learns by adjusting its internal parameters, i.e, weights with the help of a predetermined algorithm & training sets. After proper training the network may be exposed to the patterns other than the trained ones to produce consistent output. One of the important attributes is the fault tolerance, i.e., the net preserves its prediction capability even with some faulty links.

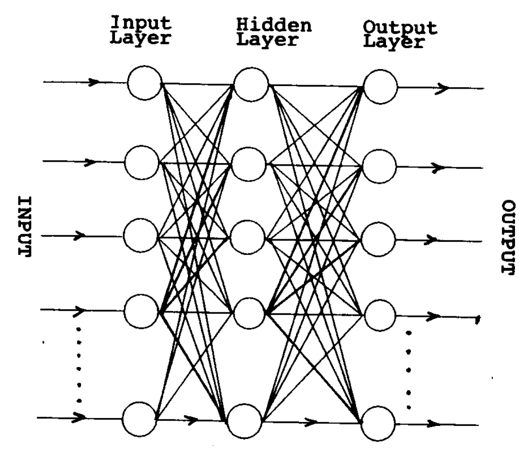


Fig. 1, A Typical Three Layer Feedforward ANN

Pattern recognition is the concurrent processing of a body of information, all items of which are available at the same time. In general, a pattern is a data structure of features, including information on feature name and feature values and explicit or implicit information on relationships among features. The patterns can be classified according to some techniques like

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Bayesian approach, distances to neighbour clusters centres, etc. The distance measure may be Euclidean distance between patterns. Sets of data can be classified into different patterns by judiciously choosing the Euclidean distances, so that similar data sets can be grouped to form a single pattern and dissimilar sets to new patterns. The Euclidean distance is determined as given below,

$$ED = \sqrt{\sum (x_i - y_i)^2} \tag{1}$$

.Where x and y are two patterns. When a new pattern is encountered, it will be included in the patterns already created provided the Euclidean distance between the two is within the threshold limit as decided earlier.

<u>Training Algorithms</u>:

Training of the network is an important feature in the neurocomputing discipline. The net should learn properly with the requisite training algorithm to achieve efficient generalization. Here the algorithms employed are backpropagation, Cauchy's and combined algorithm.

<u>Backpropagation Algorithm</u>

The activated function used is

$$f(\cdot) = A.\tanh(\cdot) \tag{2}$$

where A = Maximum value of the tangent hyperbolic function.

The output is

$$\hat{y} = f(\lambda . \underline{X} . [W]) \tag{3}$$

$\hat{y}$ = Estimated output

$\lambda$ = Weighting factor to constrain the activation in the non-linear zone.

[W] = Weight matrix between any two layers.

$\underline{X}$ = Input vector to any of the two layers

The weight adjustments are made according to the following

$$[W]_{ij}(t+1) = [W]_{ij}(t) + \eta \delta_j \underline{X}_j \tag{4}$$

where $[W]_{ij}(t)$ is the weight either from input node i to hidden node j or from hidden layer i to output layer j at any time t, $\underline{X}_j$ is either the output of node i or is an input, $\eta$ is the convergence co-efficient varied from 0.1 to 1.0, $\delta_j$ is an error term for node j.

<u>Cauchy's Algorithm</u>

The weights are updated with the help of Cauchy's distribution function in conjunction with the Boltzmann probability distribution. The weights are changed by a random value, which is given as

$$X_c = \rho(T(t) \ \tan\ [P(X)]) \tag{5}$$

where $\rho$ = learning rate co-efficient

$X_c$ = the change in weight.

$P(X)$ = a random number selected from a uniform distribution over the open interval $-\pi/2$ to $\pi/2$.

The probability of accepting this change in weight is determined from the Boltzmann distribution

$$P(c) = \exp(-c/KT) \tag{6}$$

where $P(c)$ = the probability of a change of c in the objective function which is given by

$$E_p = (1/2)\sum (d_k - y_k)^2 \tag{7}$$

where $d_k$ = the target vector.

K = constant analogous to Boltzmann's constant; the value used is $10^{-17}$.

T = The artificial temperature usually chosen to be a large value. Here it is selected as 9898.

<u>Combined backpropagation-Cauchy's Algorithm</u>

The combined algorithm explores the potential features of the two above mentioned individual algorithms. The other aspects like the activation function, the error signal and the objective function remain the same. In contrast to the other two, the weights are updated by the differential weights, partly contributed by the backpropagation and partly by Cauchy's algorithm. The weight at (t + 1)th time step is

$$[W]_{ij}(t+1) = [W]_{ij}(t) + \eta[\alpha \Delta W_{ij}(t) + (1-\alpha)\delta_j \underline{X}_j]\eta_1 + (1-\eta)x_c \tag{8}$$

$\alpha$ = Momentum co-efficient, varies from 0. to 1.0.

$\Delta W_{ij}(t)$ = Previous weight change.

$\eta$ = convergence co-efficient, when it is 1.0, the weight adjustments are due to pure backpropagation and 0.0 the weights are due to for pure Cauchy's algorithm.

$\eta_1$ = Weighting factor to control the convergence co- efficient when the change of weight is only due to backpropagation and its value varies from 0.0 to 1.

<u>IMPLEMENTATION STRATEGY</u>

The concept of connectionist model for noise canceller is extended to implement the generalized filter. The basic building blocks for the scheme are shown below in fig.2.

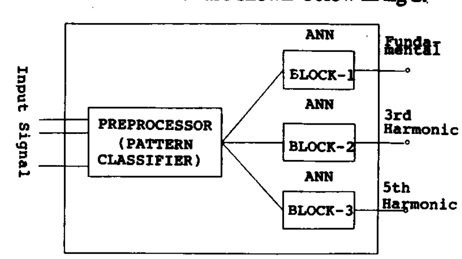


Fig. 2, Block Diagram of the Proposed Scheme.

The input samples consisting of the signals like fundamental, 3rd harmonic, 5th harmonic and noise or combination of above signals, serve as the input to the scheme. The first block, i.e., the pattern classifier classifies all the input patterns seen by it broadly into four clusters or groups. Each node or group may include one or more than one patterns. The cluster pattern is created by taking the mean of the individual patterns in the cluster. The new cluster is created by measuring the Euclidean distance between the cluster centres and the new pattern centres. Here 32 sets of data are generated by the necessary signal generation routine with four categories of signals with four different noise powers. Each subcategory consists of two sets of data. They are grouped as

1) Fundamental + noise (noise power = -5dB, -10dB, -20dB & -30 dB down the signal power)

2) Fundamental + 3rd harmonic + noise (noise power = -5dB, -10dB, -20dB & -30dB down the signal power).

3) Fundamental + 5th harmonic + noise ( noise power = -5dB, - 10dB, -20dB & -30dB down the signal power).

4) Fundamental + 3rd harmonic + 5th harmonic + noise (noise power = -5dB, -10dB, -20dB, -30dB).

These 32 sets are classified into four clusters with the pattern numbers as shown in the Table-I . However, the four clusters in the table correspond to the four categories mentioned above. Blocks 1,2 & 3 are trained with any of the patterns from clusters 1 or 2, 2 or 4 , 3 or 4 respectively with low noise power. The target vectors for the blocks 1, 2 & 3 are fundamental, 3rd harmonic and 5th harmonic respectively. Once the net is trained, it is exposed to the unknown pattern. If the Euclidean distance between the unknown pattern centre and the centre of the new cluster formed, due to 1 and 2, is within the threshold then the fundamental block is activated and the fundamental component is extracted. Similarly if the new pattern matches with clusters 2 or 4, then the 2nd block, i.e., 3rd harmonic block is activated and if pattern matches with 3 or 4, then 3rd block, i.e., the 5th harmonic block will be activated. Therefore, at a particular time and for a pattern, one block will be activated resulting one output. The above classification is based on heuristics to fit into many practical problems.

Table-I; shows the clustered patterns

| Node | Count | Pattern Numbers |
|---|---|---|
| 1 | 8 | 0,1,6,7,8,9,18,19 |
| 2 | 8 | 2,3,10,11,12,13,26,27 |
| 3 | 8 | 4,5,14,15,16,17,28,29 |
| 4 | 8 | 20,21,22,23,24,25,30,31 |

## SIMULATION

The simulation for the above scheme is carried out with MicroVAX II computing machine. The 32 sets are generated using the necessary signal generation routine. The signal generated is always of unity power. The signal model considered is

$$y(t) = \sum_{K} \sin(kwt) + V(t) \qquad (9)$$

where $k = 1,3,5,7,..n$ and $V(t)$ is zero mean white noise. The fundamental component considered here is of power frequency, i.e., 50Hz. The input sets are formed with required signal components and additive white noise. The patterns are classified using the concept of distance between the neighbourhood clusters. The thresholds for the Euclidean distance is chosen here to be 2.0. After it is classified the first block, i.e, fundamental block of the ANN is trained by employing backpropagation algorithm with input samples consisting of 1st + (-20dB) noise power. The second block is trained with input samples consisting of fundamental + 3rd harmonic + (-20dB) noise with all the three algorithms. The 3rd block is trained with the input samples consisting of fundamental + 5th harmonic + (-20dB) noise power with backpropagation algorithm. After proper training the net is exposed to new patterns and is able to extract successfully. The number of neurons in each layer is 16 for each block.

## RESULTS & DISCUSSION

Figures 3,4 & 5 show the convergence characteristics for the fundamental, 3rd harmonic & 5th harmonic respectively. The local minima trapping effect of the backpropagation algorithm is clearly depicted by fig. 4. Here objective function is trapped in local minima leading to a floor level of -10.35dB, whereas some improvement is marked with Cauchy's algorithm. But the combined algorithm converges faster and the floor level is -120dB thereby, displaying excellence of the algorithm over the other two. The fundamental component considered is shown in Fig. 6. When the net is exposed to an input consisting of 1st + 5dB noise power above the signal power, it matches with the cluster 1 and hence 1st block is activated to extract the fundamental component as displaying by fig.7. Fig 8 shows the net's filtering capability with incomplete information i.e. the even sample suppressed. When fundamental block is activated although fault occurs in the net, still the net's output is found to be consistent. The phenomenon of robustness of the net is shown in fig. 9 with 25% links opened between the layers. The extraction features for the 3rd harmonic in relevance to all the algorithms is clear from fig. 10 & 11. In fig. 10 the net trained with combined algorithm and is able to recover the desired 3rd harmonic with very low SNR. Performance of Cauchy's algorithm is better than that of backpropagation as shown in fig. 11. Fig. 12 exhibits the 5th harmonic component extraction thereby showing the 3rd block activation. The combined algorithm proposed for the scheme, however, excels over all as shown in the results presented in this paper.

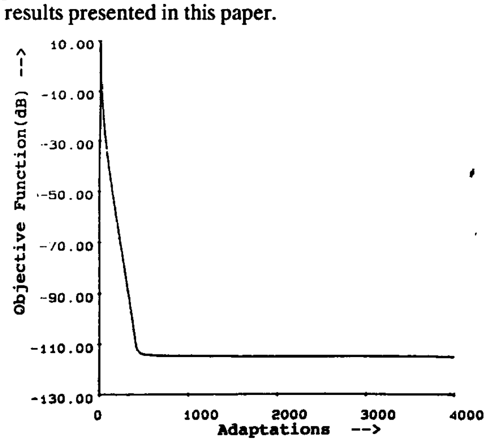


Fig. 3

Fig. 3: Learning Curve for fundamental component using backpropagation al., $\eta = 0.45, A = 3.0, \lambda = 0.0065$.

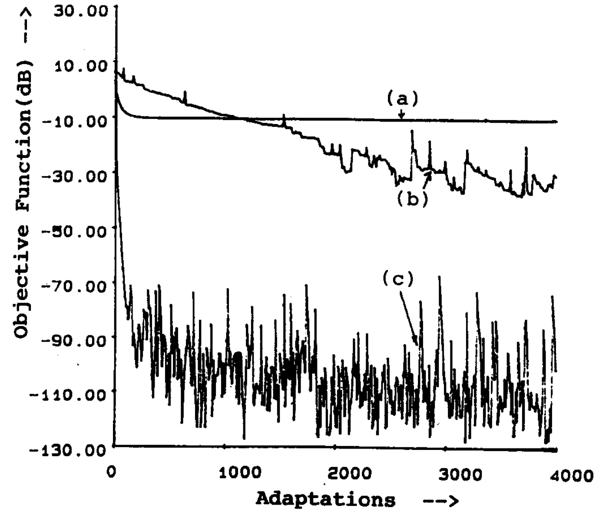


**Fig. 4**

Fig. 4: Learning Curves for third harmonic component, (a)-back-propagation, $\eta=0.5, A=2.4, \lambda=0.009$; (b)-Cauchy's al., $\rho=0.01, \lambda=0.07, A=2.0$; (c)-Combined al, $\eta=0.075, \eta_1=1.00, \rho=0.00002, \lambda=0.0008, A=3.0, \alpha=0.2$

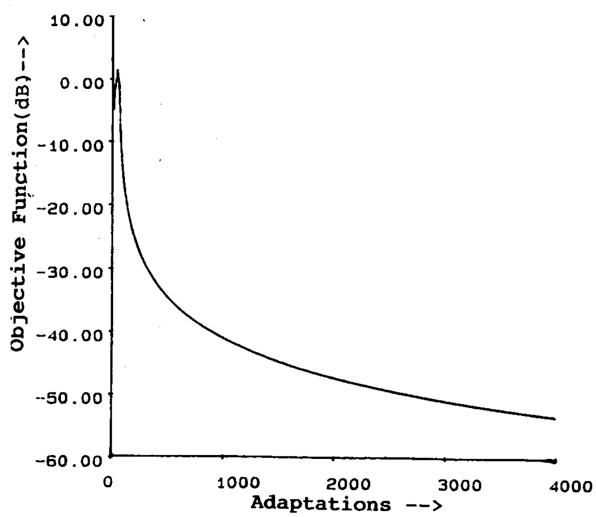


**Fig. 5**

Fig. 5: Learning Curve for 5th harmonic using backpropagation, $A=2.0, \eta=0.85, \lambda=0.007$

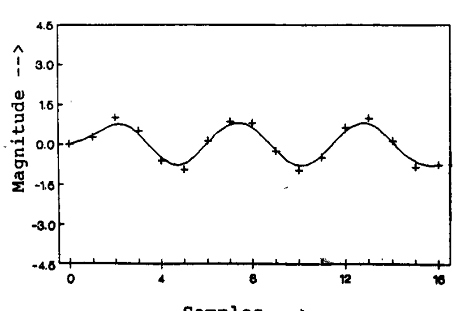


**Fig. 6**

Fig. 6: Target for 3rd harmonic Signal

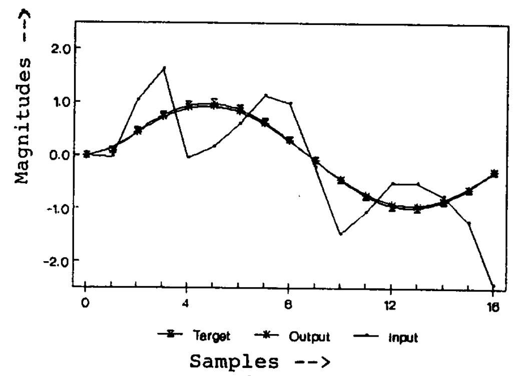


**Fig. 7**

Fig. 7: Extracted output, target and input(fundamental + 5dB noise power above thw signal power) for fundamental component using backpropagation.

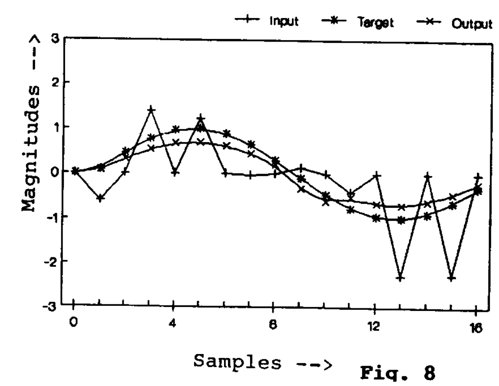


**Fig. 8**

Fig. 8: Extracted fundamental component with input signal (SNR=0dB) and even samples suppressed.

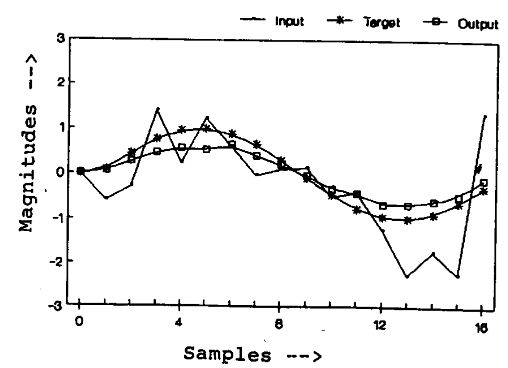


**Fig. 9**

Fig. 9: Extracted fundamental component with 25% faulty links and input signal (SNR=0dB).

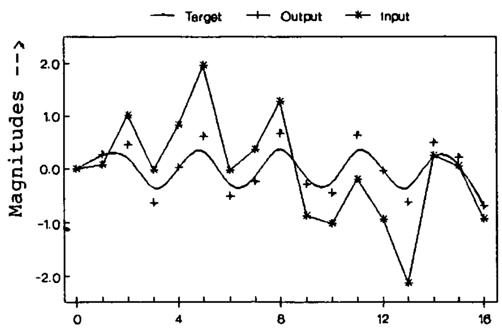


Fig. 10: Extracted third harmonic and input signal (1st + 3rd + 5dB noise power above the signal power) using combined al.

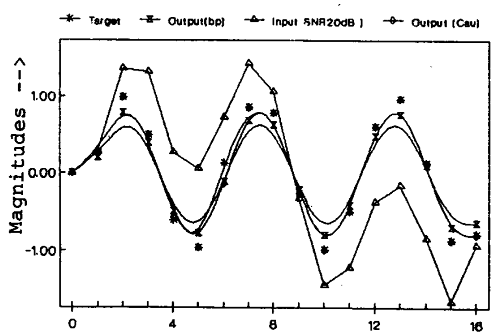


Fig. 11: Extracted third harmonic components using back-propagation and Cauhy's algorithm with input signal (1st + 3rd + noise) with SNR = 20dB.

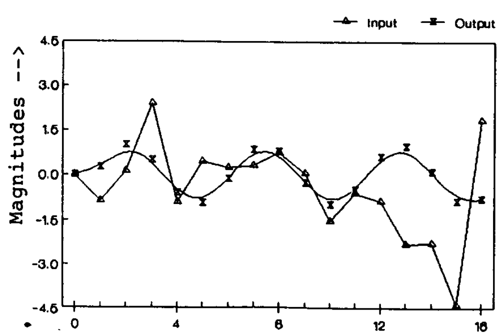


Fig. 12: Extracted 5th harmonic component with input signal (SNR = 10dB) consisting of 1st + 5th + noise using back propagation al.

## CONCLUSION

This paper proposes a generalized filter employing the concept of Pattern Recognition, based on Eucledian distance measurement and neural network. The convergences aspect is investigated by using three algorithms. It is claimed from the given results that the combined algorithm performs best, i.e., its convergence is faster than the other two. The proposed scheme is found to be robust and fault tolerant. The generalization capability is quite interesting because of its potentiality to deal with incomplete information. Improvement can be further made by adopting adaptive pattern recognition technique. Further the scheme can be made more robust by replacing the preprocessor with a neural net for pattern classification.

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